



**University of  
Zurich**<sup>UZH</sup>

**Zurich Open Repository and  
Archive**

University of Zurich  
University Library  
Strickhofstrasse 39  
CH-8057 Zurich  
[www.zora.uzh.ch](http://www.zora.uzh.ch)

---

Year: 2006

---

## **A neural network inversion of the DART model to retrieve Norway spruce LAI at a very high spatial resolution**

Zurita-Milla, R ; Malenovský, Z ; Homolová, L ; Schaepman, Michael E ; Martin, E ;  
Gastellu-Etchegorry, J P ; Clevers, J G P W ; Cudlín, P

**Abstract:** Leaf Area Index (LAI) is a key input parameter in many eco-physiological and climate models. Therefore, the development of methods to accurately and timely retrieve LAI over large areas is essential to fully understand the Earth system. The inversion of radiative transfer models is a “universal” method to retrieve LAI from remotely sensed images because it is independent from the study area and the sampling conditions. In this paper, we study the potential of the 3D Discrete Anisotropic Radiative Transfer (DART) model to retrieve the LAI of a Norway spruce forest stand. An extensive airborne/field campaign was carried out in September 2004 to acquire AISA Eagle VNIR hyperspectral images (pixel size of 0.4 m) and to collect ground truth data for the image pre-processing, DART parameterization and validation of the LAI estimations. Because DART is a complex and computationally demanding model, it was first run in direct mode to build a large dataset of possible canopy realizations. Then, a relatively simple two-layer feed forward backpropagation neural network was trained using the simulated DART top of canopy reflectances and a priori information on canopy closure. Finally, the LAI inversion was performed over the radiometrically and atmospherically corrected AISA Eagle images by using a sliding window whose size matches the extent of the DART modelled forest scenes. Results indicate that the inversion of the DART model to retrieve the LAI of complex Norway spruce canopies using ANN is a promising tool. Nevertheless, the approach still has to be improved in case of very high spatial resolution images.

Posted at the Zurich Open Repository and Archive, University of Zurich

ZORA URL: <https://doi.org/10.5167/uzh-77587>

Conference or Workshop Item

Published Version

Originally published at:

Zurita-Milla, R; Malenovský, Z; Homolová, L; Schaepman, Michael E; Martin, E; Gastellu-Etchegorry, J P; Clevers, J G P W; Cudlín, P (2006). A neural network inversion of the DART model to retrieve Norway spruce LAI at a very high spatial resolution. In: The Second International Symposium on Recent Advances in Quantitative Remote Sensing, Torrent (E), 25 September 2006 - 29 September 2006, 84-95.

# A neural network inversion of the DART model to retrieve Norway spruce LAI at a very high spatial resolution

R. Zurita-Milla (1,\*), Z. Malenovský (1,2,\*), L. Homolová (2), M. E. Schaepman (1), E. Martin (3), J.P. Gastellu-Etchegorry (3), J.G.P.W. Clevers (1) and P. Cudlín (2)

(1) Centre for Geo-Information (CGI), Wageningen University, P.O. Box 47, 6700 AA Wageningen, The Netherlands.

(2) Institute of Systems Biology and Ecology, Academy of Sciences of the Czech Republic, Na Sádkách 7, 370 05 České Budějovice, Czech Republic.

(3) Centre d'Etudes Spatiales de la Biosphère (CESBIO), UPS-CNRS-CNRS-IRD, 18 Avenue Edouard Belin, BPI 2801, 31401 Toulouse, Cedex 9, France

\*E-mail corresponding authors : raul.zurita-milla@wur.nl; zbynek.malenovsky@wur.nl

**ABSTRACT-** Leaf Area Index (LAI) is a key input parameter in many eco-physiological and climate models. Therefore, the development of methods to accurately and timely retrieve LAI over large areas is essential to fully understand the Earth system. The inversion of radiative transfer models is a “universal” method to retrieve LAI from remotely sensed images because it is independent from the study area and the sampling conditions. In this paper, we study the potential of the 3D Discrete Anisotropic Radiative Transfer (DART) model to retrieve the LAI of a Norway spruce forest stand. An extensive airborne/field campaign was carried out in September 2004 to acquire AISA Eagle VNIR hyperspectral images (pixel size of 0.4 m) and to collect ground truth data for the image pre-processing, DART parameterization and validation of the LAI estimations. Because DART is a complex and computationally demanding model, it was first run in direct mode to build a large dataset of possible canopy realizations. Then, a relatively simple two-layer feed forward backpropagation neural network was trained using the simulated DART top of canopy reflectances and a priori information on canopy closure. Finally, the LAI inversion was performed over the radiometrically and atmospherically corrected AISA Eagle images by using a sliding window whose size matches the extent of the DART modelled forest scenes. Results indicate that the inversion of the DART model to retrieve the LAI of complex Norway spruce canopies using ANN is a promising tool. Nevertheless, the approach still has to be improved in case of very high spatial resolution images.

## 1. INTRODUCTION

Information on canopy leaf area index (LAI) is required for a number of applications. For instance, LAI is one of the key input parameters in many eco-physiological and climate models (Hoffmann and Jackson, 2000; Kucharik et al., 2000). LAI is defined as the total one-sided leaf area per unit of ground surface area. However, in the case of coniferous non-flat leaves, used in this study, we consider LAI to be half of the total intercepting leaf area per unit ground surface area (Chen and Black, 1992).

Radiative transfer (RT) models offer a “universal” method to retrieve canopy LAI from optical remotely sensed data. One can use a 1D RT model in case of a horizontally homogeneous canopy, i.e. grasslands or some homogeneous agricultural crops. Nevertheless, 1D RT models can not account for the structural complexity of forest ecosystems, therefore, 3D RT models were introduced (Gastellu-Etchegorry et al., 1996). In this work, we analysed a Norway spruce (*Picea abies* (L.) Karst.) forest stand, which represents one of the most structurally heterogeneous ecosystem. Unfortunately, the majority of the current 3D RT models do not allow an

ecologically appropriate structural characterization of forests at very high spatial resolution. In this respect, the 3D Discrete Anisotropic Radiative Transfer (DART) model (Gastellu-Etchegorry et al., 2004) has been recently modified to incorporate a selection of eco-physiological tree structural characteristics like inner and peripheral crown defoliation, heterogeneous distribution of foliage in vertical and horizontal directions, branches of first order and small woody twigs, etc. These features are expected to increase the reliability of the model simulations and allow a more accurate retrieval of forest stand biophysical parameters in case of very high spatial resolution image data (pixel size < 1 m).

The objective of this study was to design a methodological approach to estimate LAI of Norway spruce stands from the spectral information acquired by an airborne hyperspectral sensor at very high spatial resolution (pixel size of 0.4 m). The approach was based on the use of artificial neural networks (ANN) because they are computationally efficient (i.e., suited to derive operational products) and able to accurately approximate complex non-linear relationships (Weiss et al., 2002; Schlerf and Atzberger, 2006).

## 2. STUDY AREA AND DATASETS

### 2.1 Study area and ground data collection

A montane Norway spruce forest stand growing at the permanent experimental research site Bily Kriz in the Moravian-Silesian Beskydy Mountains was selected to illustrate this study (Pavelka et al., 2003). More precisely, the study area is situated in the eastern part of the Czech Republic bordering with Slovakia (18.54°E, 49.50°N; altitude 936 m above sea level) (Figure 1). The average annual air temperature is about 5.5°C, the average annual precipitation amounts around 1000-1400 mm. The forest stand is made of a regularly spaced plantation of Norway spruce (*Picea abies* (L.) Karst.) trees established with three years old spruce seedlings in 1981. In 2004, these trees were 26 years old, about 10 m tall and they had an average diameter at breast height (DBH) of 12.8 cm.



**Figure 1.** Geographic position of the experimental research site Bily Kriz (Europe, East border between Czech Republic and Slovakia).

### 2.2 Hyperspectral data

An extensive airborne and field campaign was carried out in September 18<sup>th</sup>, 2004 at the Bily Kriz research site in order to acquire multi-directional aerial AISA Eagle (Spectral Imaging, SPECIM Ltd., Finland) VNIR hyperspectral images with pixel size of 0.4 m (64 spectral bands with a Full-Width-Half-Maximum (FWHM) of about 10 nm). The information necessary for the radiometric and atmospheric corrections, and for geo-orthorectification of the AISA images was gathered simultaneously with the sensor over flight. The digital numbers (DN) of the AISA images were corrected for the sensor random noise and then transformed into radiance values using sensor calibration files and the CaliGeo software. Subsequently, the atmospheric correction was applied to convert at-sensor radiances into surface reflectance values. This correction was performed with the ATCOR-4 model (Richter and Schlapfer, 2002). A software tool of ATCOR-4 was also used to correct the brightness reflectance gradient within the airborne images in the across-track direction.

This operation transformed the data into bidirectional reflectance factor (BRF). Finally, the AISA Eagle images were classified using a maximum likelihood classifier in three classes: background, sunlit and shaded crowns. This classification was used to estimate the canopy closure (CC) of the Norway spruce forest stand.

### 2.3 LAI ground measurements

In September 2004, ground measurements of LAI were done over the forest stand under study. A Li-Cor Plant Canopy Analyser, LAI-2000, and hemispherical colour images, taken with a digital camera equipped by fish-eye lens, were used for this purpose (Malenovský et al., 2006). The hemispherical images were processed using the CAN-EYE software (Jonckheere, 2004; Weiss, 2004).

## 3. DART INVERSION

The 3D Discrete Anisotropic Radiative Transfer (DART) model was inverted using an artificial neural network (ANN) approach. First a number of DART simulated images were generated to train an ANN to predict LAI. After that, the ANN was used to retrieve LAI from the AISA Eagle hyperspectral image (c.f. section 2.2).

### 3.1 DART parameterization

Most of the ground data required for a detailed parameterization of the DART model was collected at the test site during September 2004. Ancillary allometric and eco-physiological measurements of the tree crowns were obtained earlier, during a field campaign carried out at the same research site in the summer of 1997 (Pokorný & Marek, 2000). Mock-ups of Norway spruce forest stand, represented by three-dimensional plots covering an area of 6 by 6 m, were constructed using four trees in case of CC = 55% and up to seven trees in case of CC = 95%. The Norway spruce trees were simulated with a total height between 9 – 11 m. Each tree crown was created out of 11 horizontal levels associated with specific average leaf angles (from 25° to 40°) and own leaf optical properties (reflectance, transmittance, and absorption). The leaf optical properties were measured in laboratory using an ASD FieldSpec Pro spectroradiometer connected to the Li-Cor integrating sphere Li-1800-12. They were generated for each crown level according to mutual ratio between present leaf generations and ratio of leaves exposed to direct and diffuse illumination. Field destructive measurements were used to parameterise the vertical and horizontal leaf distributions, spatially specific crown defoliation, as well as the distribution of the woody crown parts (i.e., cones representing trunks, pyramids representing branches of first order – branches growing directly from trunks, and woody turbid media representing small tiny twigs with twig average angle of 35°). The forest stand background was designed as a

mixture of bare soil and needle litter, and modelled as the continuous slope of 13.5°. All the optical properties of leaves, bark of trunks and branches, and forest background were measured and consequently defined in DART as to be of Lambertian nature. The radiative transfer through the atmosphere above the forest stand was not included. Therefore, the DART simulated spectral bands, corresponding to AISA Eagle bands (Table 1), represent the top of canopy (TOC) BRF.

**Table 1.** List of DART simulated spectral bands.

Band	Central wavelength [nm]	FWHM [nm]
1	468.83	9.00
2	559.08	9.20
3	670.74	9.33
4	726.76	9.35
5	754.88	9.51
6	783.44	9.52
7	840.51	9.49

### 3.2 DART simulated images

Because DART is a very complex and computationally demanding model, we decided to only run a reduced number of canopy realizations. The parameters selected to produce these canopy realizations were chosen to cover the plausible range of parameter values present in the study area.

Table 2 shows the range of canopy closures (CC), sun zenithal angles, tree spatial distributions and LAI values that were chosen to generate the DART simulated images. The combination of these parameters led to 650 DART simulated images.

**Table 2.** Configurations of the DART simulations.

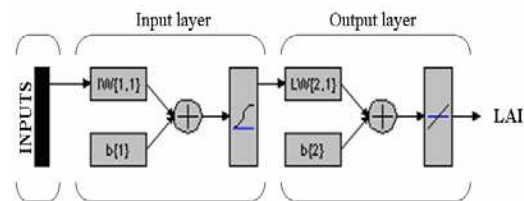
Variable	Simulated range
Canopy closure [%]	55 – 95 (steps of 10)
Solar azimuth [°]	131,154,176,199 & 221
LAI [m2/m2]	3 – 15 (steps of 1)
Tree distribution [–]	Regular & irregular



**Figure 3.** RGB colour composite (bands 3, 2, 1) of a DART simulated image (light blue = tree crowns, red = background, black = shadowed areas).

### 3.3 ANN Architecture and training

The first step in any approach that uses ANN is to decide the architecture or configuration of the network (i.e., how many layers, how many neurons, learning functions, etc.). The performance of several ANN architectures was tested using the neural network toolbox available in MATLAB®. A two-layer feedforward backpropagation neural network was finally selected for the analysis. A log-sigmoidal transfer function was used in the first layer and a linear transfer function in the output layer.



**Figure 2.** Architecture of the ANN used for retrieval.

The network was trained using the DART simulated images and *a priori* knowledge on the canopy closure (CC). Before the training of the network, the BRF and the CC data were pre-processed so that they have a zero mean and a standard deviation of 1. Then a principal component analysis (PCA) was applied to the normalized data and the components that contribute less than 2% of the total variance were removed. The remaining number of inputs was used to decide the number of neurons of the first layer, because each input requires a neuron. The output layer consisted of one neuron, because we are only interested in predicting one variable – LAI (Figure 2). The Levenberg-Marquardt optimization algorithm was selected for the training of the network because it is very fast although it requires a large amount of memory.

Overfitting is one of the main problems that can occur during the training of any ANN. When overfitting happens, the network is very precise to reproduce the

outputs that have been previously presented to it, but when new data (i.e. data not used during the training) is presented to the network then the error of the network is very large. In short, the ANN lacks generalization because it has become too specialised during the training. To avoid this, we applied an early stopping technique during the training. This means that a validation dataset is presented to the network simultaneously to the training dataset and when the error of the validation dataset is above a certain threshold then the training of the network is stopped (even though the error of the training dataset might still be declining).

The 650 DART simulated images were split into 3 groups: training, validation and testing. For the two last groups we used all the DART simulations that were done with LAI of 4, 9 and 14. This means that 150 simulations were assigned to the validation and testing groups and that 500 simulations were used for the training of the ANN. Subsequently, the 150 simulations were randomly assigned to the validation (80%) and testing (20%) groups.

#### 3.4 LAI retrieval

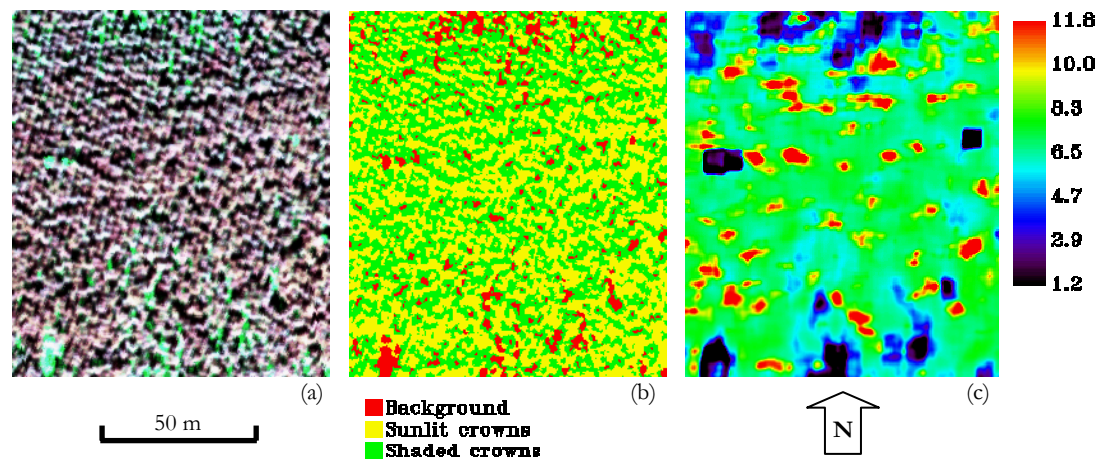
A sliding window of 6 by 6 m was applied to the AISA Eagle hyperspectral image to obtain the BRF data in the

seven wavelengths that were simulated with DART. The same sliding window was applied to the AISA classified image to compute the CC over that area ( $CC = 100 \times \text{vegetation pixels} / \text{total number of pixels}$ ). Then, the BRF and the CC data were processed using the transformation parameters obtained during the pre-processing of the ANN inputs (c.f., section 3.3). Finally the transformed data was presented to the ANN to retrieve the LAI of the 6 by 6 m area. An LAI map of the study area was produced by repeating these operations for all the pixels of the image.

## 4. RESULTS AND DISCUSSION

### 4.2 Training of the ANN

As described in section 3.3., the ANN was trained using DART simulated images and *a priori* information on canopy closure (CC). Figure 3 shows, as an example, one of the 650 DART simulated images. In these images one can identify the sunlit and the shaded areas of the scene represented by tree crowns and background. Nevertheless, in this study we did not use this spatial information, but only the mean BRF values of the DART images.



**Figure 4.** RGB colour composite (bands 5, 3, 2) of the AISA Eagle hyperspectral image over the study area (a); result of Maximum likelihood classification (b); and LAI map of the spruce canopy (c).



The normalization and PCA analysis of the BRF and CC datasets reduced their dimensionality from 8 to 7. This means that 7 neurons were finally used in the input layer of the ANN.

#### 4.1 LAI retrieval and validation

The retrieval of LAI was done by employing the AISA Eagle hyperspectral image to generate the inputs needed to run the ANN. First, using a sliding window of 6 by 6 m, the BRF and CC information was extracted. Then, this input data was pre-processed using the transformation coefficients obtained during the training of the network. After that, this data was presented to the trained ANN to predict the LAI over the 6 by 6 m area. Finally, an LAI map was produced by iterating this operation for all the pixels of the study area (Figure 4c).

One can visually interpret, by comparing Figures 4b and 4c, that the spatial pattern of the LAI map appears to match the general pattern of the AISA classified image. This means that pixels classified as background correspond with areas of low LAI, while tree crowns pixels have average or high LAI values. However, when we plotted the LAI values estimated from the AISA image for the 14 positions where we collected ground LAI data and the ground LAI values, obtained using the LAI-2000 device and the CAN-EYE software, we could not find a good match (Figure 5). Cross-validation of the ANN LAI values against the LAI-2000 or the CAN-EYE LAI values revealed very low regression relationships with statistically insignificant coefficients of determination. Nevertheless, it is also important to mention that the comparison of both ground LAI measurements did not showed any correlation either. This finding suggests that the ground LAI

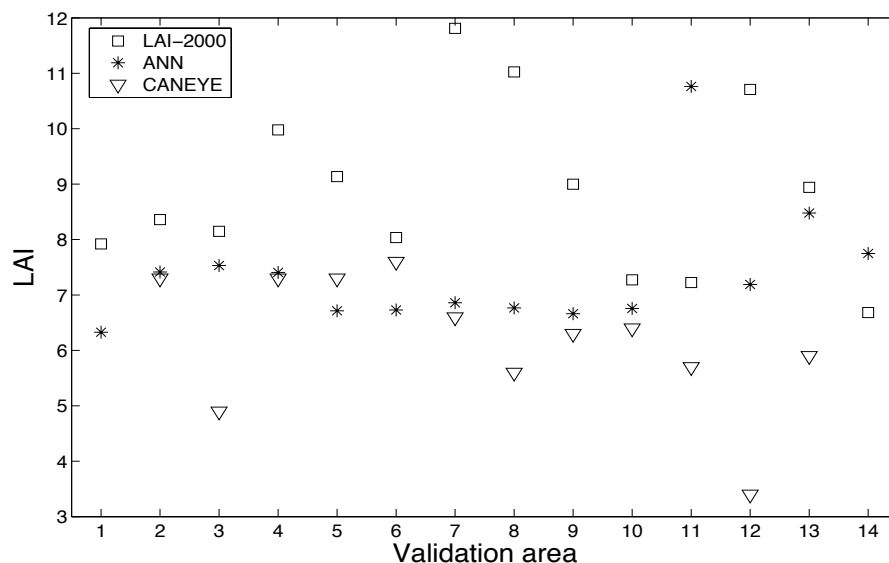
measurements present large uncertainties or errors. Such uncertainties/errors might have been introduced either by the set-up of measurements or by the type of canopy – a complex coniferous forest stand.

#### 5. CONCLUSIONS

In this study we have presented a methodological approach to retrieve LAI of complex coniferous forest canopies from hyperspectral data of very high spatial resolution (pixel size of 0.4 m). The approach relies on the use of artificial neural networks (ANN) to invert the 3D radiative transfer model DART. First the DART model was parameterized using ground data collected during an extensive field campaign. Then, a number of DART simulated images were produced to train a relatively simple two-layer feedforward backpropagation network. After that, we retrieved the LAI of a Norway spruce canopy acquired with the AISA Eagle hyperspectral sensor. Finally, the retrieved LAI values were validated against ground measurements collected with an LAI-2000 device and with a digital camera equipped by a hemispherical (fish-eye) objective.

Results of this study pointed out the following particular conclusions:

1. If correctly parameterised, the DART model is able to simulate complex forest canopies.
2. ANN are a promising tool to operationally retrieve LAI from remotely sensed data.



**Figure 5.** Validation of LAI estimated from hyperspectral high spatial resolution data (ANN) against ground measurements (LAI-2000 and CAN-EYE).

3. The cross-validation of remote sensing based LAI estimations with ground measurements is not straightforward, because ground devices like the LAI-2000 might suffer from systematic biases and/or non-systematic errors, especially in case of a dense coniferous forest canopy.
4. The retrieval of Norway spruce LAI from very high spatial resolution hyperspectral data is still a challenge. In this respect, new approaches making simultaneous use of both the spatial and the spectral information present in hyperspectral images might further improve the accuracy of the canopy LAI estimations.

#### ACKNOWLEDGEMENTS

The authors would like to acknowledge the access to the METACentrum computing cluster facilities (Brno, Czech Republic), provided under the research intent MSM6383917201. The contribution of R. Zurita-Milla is granted through the Dutch SRON GO programme (EO-061).

#### REFERENCES

- Chen, J. M., and Black, T. A., 1992, Defining leaf area index for non-flat leaves. *Plant, Cell and Environment*, 15, 421-429.
- Gastellu-Etchegorry, J. P., Demarez, V., Pinel, V., and Zagolski, F., 1996, Modeling radiative transfer in heterogeneous 3-D vegetation canopies. *Remote Sensing of Environment*, 58, 131-156.
- Gastellu-Etchegorry, J. P., Martin, E., and Gascon, F., 2004, DART: a 3D model for simulating satellite images and studying surface radiation budget. *International Journal of Remote Sensing*, 25, 73-96.
- Hoffmann, W. A., and Jackson, R. B., 2000, Vegetation-climate feedbacks in the conversion of tropical savanna to Grassland. *Journal of Climate*, 13, 1593-1602.
- Jonckheere, I., 2004, Review of methods for in situ leaf area index determination Part I. Theories, sensors and hemispherical photography. *Agricultural and Forest Meteorology*, 121, 19-35.
- Kucharik, C. J., Foley, J. A., Delire, C., Fisher, V. A., Coe, M. T., Lenters, J. D., Young-Molling, C., Ramankutty, N., Norman, J. M., & Gower, S. T., 2000, Testing the performance of a Dynamic Global Ecosystem Model: Water balance, carbon balance, and vegetation structure. *Global Biogeochemical Cycles*, 14, 795-825.
- Malenovsky, Z., Martin, E., Homolová, L., Gastellu-Etchegorry, J. P., Zurita-Milla, R., Schaepman, M. E., Pokorný, R., Clevers, J. G. P. W., and Cudlin, P., 2006, Influence of woody elements of a Norway spruce canopy on nadir reflectance simulated by the DART model at very high spatial resolution. *Remote Sensing of Environment*, accepted.
- Pavelka, M., Janouš, D., Urban, O., Acosta, M., Pokorný, R., Havráňková, K., & Formánek, P., 2003, Carbon sources in vertical profile of a norway spruce stand. *Folia Oecologica*, 30, 199-206.
- Pokorný, R., & Marek, M. V., 2000, Test of accuracy of LAI estimation by LAI-2000 under artificially changed leaf to wood area proportions. *Biologia Plantarum*, 43, 537-544.
- Richter, R., and Schlapfer, D., 2002, Geo-atmospheric processing of airborne imaging spectrometry data. Part 2: atmospheric/topographic correction. *International Journal of Remote Sensing*, 23, 2631-2649.
- Schlerf, M. and Atzberger, C., 2006, Inversion of a forest reflectance model to estimate structural canopy variables from hyperspectral remote sensing data. *Remote sensing of environment*, 100, 281-294.
- Weiss, M., 2004, Review of methods for in situ leaf area index (LAI) determination Part II. Estimation of LAI, errors and sampling. *Agricultural and Forest Meteorology*, 121, 37-53.
- Weiss, M., Baret, F., Leroy, M., Hautecoeur, O., Bacour, C., Prevot, L., and Bruguier, N., 2002, Validation of neural net techniques to estimate canopy biophysical variables from remote sensing data. *Agronomie*, 22, 547-553.